

Dis 11 ER + Inference

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Estimation methods (MAP, MLE)

Motivating example: Good doctor

A patient has symptom s . Being a good doctor, you want to infer the most probable cause c . (Suppose symptoms come from RV S and causes come from RV C . That is, patient has symptom $S=s$ and cause $C=c$.)

Mathematically, you'd want to find:

$$c^* = \underset{c}{\operatorname{argmax}} \Pr(C=c | S=s) = \underset{c}{\operatorname{argmax}} \left(\frac{\Pr(S=s | C=c) \Pr(C=c)}{\Pr(S=s)} \right)$$

MAP

"have more info"

situation, where

we don't know anything about C
uniform

$$c^* = \underset{c}{\operatorname{argmax}} \Pr(S=s | C=c) \Pr(C=c)$$

$$= \underset{c}{\operatorname{argmax}} \Pr(S=s | C=c) \Pr(C=c)$$

$$\text{from med. school books} \quad \text{prior}$$

$$\text{solve } \frac{d}{dc} \left[\Pr(S=s | C=c) \Pr(C=c) \right] = 0$$

sometimes, $\Pr(C=c | S=s)$ is PDF w/ form $e^{-\lambda x}$
to deal w/ exp, use $\ln(\cdot)$ \leftarrow useful trick

$$= \underset{c}{\operatorname{argmax}} \ln(\Pr(S=s | C=c) \Pr(C=c))$$

$c = \text{'cold' up 9ly.}$

$$= \underset{c}{\operatorname{argmax}} \Pr(S=s | C=c)$$

MLE

if we didn't know the $\Pr(C=c)$

$$c^* = \underset{c}{\operatorname{argmax}} \Pr(S=s | C=c) \Pr(C=c)$$

const,

c_1, c_2, c_3, \dots

3. MLE & MAP for Continuous Random Variables

Let X be an exponentially distributed random variable with mean 1. Given X , the random variable Y is exponentially distributed with rate X .

(a) Find MLE[X | Y].

(b) Find MAP[X | Y].

$$\begin{aligned} \text{(a) } x^* &= \underset{x}{\operatorname{argmax}} \Pr(Y=y | X=x) f_{Y|X}(y | x) \\ &= \underset{x}{\operatorname{argmax}} x e^{-y/x} \end{aligned}$$

$$f_{Y|X}(y | x) \sim \text{Exp}(x)$$

$$= \underset{x}{\operatorname{argmax}} \quad (\cancel{x e^{-y x}})$$

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$$= \underset{x}{\operatorname{argmax}} \quad \ln(x e^{-y x})$$

$$= \underset{x}{\operatorname{argmax}} \quad (\ln x) + (-yx)$$

$$\frac{d}{dx} \ln x - yx = 0 \Rightarrow \frac{1}{x} - y = 0$$

$$\boxed{x = \frac{1}{y}}$$

b2 $\ln \mathbb{E}[X|Y] = \frac{1}{Y}$

b) $x^* = \text{MAP}(X | Y = y)$

$$= \underset{x}{\operatorname{argmax}} \quad \frac{f_{Y|X}(y|x)}{f_X(x)} \sim \text{Exp}(1)$$

$$= \underset{x}{\operatorname{argmax}} \quad x e^{-yx} \cdot 1 e^{-1x}$$

$$= \underset{x}{\operatorname{argmax}} \quad (\ln x) + (-yx) - x$$

$$\frac{d}{dx} (\ln x - yx - x) = 0 \Rightarrow \frac{1}{x} - y - 1 = 0$$

1. Generating Erdős-Renyi Random Graphs

True/False: Let G_1 and G_2 be independent Erdős-Renyi random graphs on n vertices with probabilities p_1 and p_2 , respectively. Let $G = G_1 \cup G_2$, that is, G is generated by combining the edges from G_1 and G_2 . Then, G is an Erdős-Renyi random graph on n vertices with probability $p_1 + p_2$.

assume $p_1 + p_2 \leq 1$

ER graph $G(p)$

edges $e \in E$



each edge e exists w.p p

↑ doesn't exist w.p $1-p$

(i) possible edges

$$\rightarrow \boxed{x^* = \frac{1}{y+1}}$$

$$\Rightarrow \text{MAP}(X|Y) = \frac{1}{Y+1}$$

$$\forall e' \in E(G)$$

$$e' \text{ doesn't exist} \equiv \underline{e' \text{ not in } G_1 \wedge}$$

$$\Rightarrow P(e' \text{ doesn't exist}) = \underline{(1-p_1)(1-p_2)}$$

$$\text{if } G \text{ were ER } G(n, p_1 + p_2) \quad \neq \quad 1 - p_1 - p_2$$

$$\forall e \in E(G), P(e \text{ not existing}) = 1 - p_1 - p_2$$

$$P(e \text{ existing}) = \square \neq p_1 + p_2 \Rightarrow G \neq \text{ER}$$

2. Random Graph

Consider a random undirected graph on n vertices, where each of the $\binom{n}{2}$ possible edges is present with probability p independently of all the other edges (i.e. an Erdős-Renyi random graph). If $p = 0$ we have a fully empty graph with n completely disconnected vertices; in contrast, if $p = 1$, every edge exists, the network is an n -clique, and every vertex is a distance one from every other vertex.

- Fix a particular vertex of the graph, and let D be a random variable which is equal to the degree of this vertex. What is the PMF of D ? Calculate $\lambda \triangleq \mathbb{E}[D]$.
- Assume that $c = np$ is a constant, independent of n . For large values of n , how you would approximate the PMF of D ?

$$a) D \sim \text{Bin}(n-1, p) \Rightarrow \lambda = \mathbb{E}[D] = (n-1)p$$

$$b) D \sim \text{Poi}(\lambda) \quad \lambda = \lim_{n \rightarrow \infty} \frac{p_n}{n} = c$$

$$\begin{aligned} c^+ &= \underset{c}{\underset{\substack{\text{most probable}}}{\arg \max}} \Pr(C=c | S=s) \\ &= \underset{c}{\arg \max} \Pr(C=c | S=s) \\ &= \underset{c}{\arg \max} \frac{\Pr(S=s | C=c) \Pr(C=c)}{\Pr(S=s)} \end{aligned}$$

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A patient has symptom s . Being a good doctor, you want to infer the most probable cause c . (Suppose symptoms come from RV S and causes come from RV C . That is, patient has symptom $S = s$, and cause $C = c$)

Mathematically, you want to find:

called MAP . . .

$$c^* = \text{MAP}(C | S=s)$$

called MAP . . .

$$c^* = \underbrace{\text{MAP}(c | s=s)}_{\text{new situation}}$$

what if don't know $\Pr(c=c)$
assume $\Pr(c=c)$ is uniform

$$c^* = \arg\max_c \frac{\Pr(s=s | c=c) \Pr(c=c)}{\Pr(s=s)}$$

$$= \arg\max_c \Pr(s=s | c=c)$$
MLE($c | s=s$)